Think Pink?
The Effects and Efficiency of Breast Cancer Awareness Campaigns

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July 28, 2014

Abstract

October is National Breast Cancer Awareness Month. Using a 5% sample of Medicare claims data we find that October (and November) are associated with a 25% increase in the utilization of mammograms relative to the "average" month. We find that the "October" cohort is less likely to be diagnosed with breast cancer, somewhat more likely to be diagnosed with Stage 0 breast cancer conditional upon diagnosis, but have similar 1, 2 and 3 year mortality and similar late stage diagnosis, both conditional upon diagnosis. A model of a policy intervention to increase mammography rates suggests that among women with breast cancer who do not receive regular mammograms there is a two percentage point increase in 5-year survival. The proposed policy intervention is associated with an increase of $1,000 in expected total medical expenditure per breast cancer patient over 5 years.

JEL Codes: I11, I18, H4

Keywords: breast cancer, mammograms, screening, public health campaigns

*We are indebted to colleagues in the Bureau of Economics for providing useful comments and feedback. We would also like to thank David Vanness for his thoughts and comments. The views expressed in this article are those of the author and do not necessarily reflect those of the Federal Trade Commission. Corresponding author: Thomas Koch, 600 Pennsylvania Avenue, NW, Washington, DC 20580. Phone: 512-809-8014; E-mail: tkoch@ftc.gov.

1 Introduction

National Breast Cancer Awareness Month (NBCAM) was founded in 1985. The goal was to bring together many organizations to help raise awareness of breast cancer, and in particular, raise awareness of the value of screening including mammography, self-exams and clinical breast exams [Miller, 1998]. NBCAM now has a dozen collaborating organizations, including the American Cancer Society, American College of Obstetricians and Gynecologists, major fundraising organizations, such as the Komen Foundation, as well as a non-profit group affiliated with AstraZeneca. NBCAM has sponsorships with the NFL,[1] which features pink on-field apparel during October, and numerous charity races and walks across the United States.

Not surprisingly, the intensity of this public health awareness campaign has consequences. As has been found previously [Jacobsen and Jacobsen, 2011, McBean, 2012], NBCAM coincides with a large spike in the number of mammograms. Consequently, the number of women diagnosed with breast cancer increases with NBCAM. However, what is not known, and we measure for the first time, is whether rate of diagnosis per mammogram varies with NBCAM, and if the staging and treatment patterns vary with it as well. Because the use of mammograms as a diagnostic tool for screening is controversial (as we discuss below), changes in the selection into mammograms associated with NBCAM may have consequences for the efficacy and efficiency of those mammograms, and, thusly, NBCAM itself.

Using the 5% Sample of Outpatient Claims from Medicare for 2005-10, we measure the patterns of diagnoses and care associated with mammograms that occur during and just after NBCAM. We find, consistent with previous work, that the number of mammograms performed in October and November increase roughly twenty-five percent, relative to other months. This increase in screening appears to be associated with a decrease in the risk faced by women. Women who receive mammograms in these months are ten percent less likely to be subsequently diagnosed with breast cancer. This difference in diagnosis is pronounced among women with no other risk factors for breast cancer. This differential screening is not associated with the subsequent mortality of women, whether diagnosed with breast cancer or not. While women who receive mammograms in the peak months of October and November are more likely to be initially diagnosed with early-stage breast cancer, they are just as likely to be eventually staged with later stages.

This paper uses changes in mammography rates and initial staging conditional upon diagnoses associated with NBCAM to identify and estimate the impact of a policy that

[1] Tellingly, the NFL's website for its work with NBCAM has the tag line "A Crucial Catch: Annual Screening Saves Lives"

increases mammography rates among women who do not receive regular mammograms. Initial estimates suggest that such a policy intervention will increase 5-year survival rates among such women with breast cancer by two percentage points. An increase from 90.5% to 92.4%. The policy would be associated with an increase in total medical expenditure per woman with breast cancer of $1,000 over a five year period. A women with breast cancer who is induced to have a mammogram will expect to have $73,268 in medical expenditures accounting over the next five years in net present value terms. Where these expenditures include both those paid by Medicare and her out-of-pocket expenses. If the same women with breast cancer, is not induced to have a mammogram then her expected medical expenditures will be $72,320. The results suggest that a policy intervention that increases mammography rates in this way is cost effective if the value of a life-year is greater than $47,000 per year.

Each year approximately 210,000 women (mostly) are diagnosed with breast cancer and every year approximately 40,000 women die of the disease.[2] Today the US Preventative Services Task Force recommends that all women aged 50 to 75 get regular mammograms every two years.[U.S. Preventive Services Task Force, 2009] Approximately three quarters of women in this age group actually follow the USPSTF's recommendations. [Centers for Disease Control and Prevention, 2012]

The USPSTF's recommendations are based on various studies including a large and long randomized control trial conducted in Sweden. In the early 80s over 130,000 women aged 40 to 74 from two Swedish counties were randomized into two treatments. The first treatment group received an invitation to have regular mammography screening, while the other treatment group received usual care. The trial lasted approximately seven years. For every 10 women that died of breast cancer in the usual care group, 7 women died of breast cancer in the mammography invitation group [Tabár et al., 2011]. Despite these findings screening remains controversial.

Critiques of general mammography screening have raised two major concerns. First, authors point out that while mammography is associated with large increases in early stage diagnosis rates it is not associated with similarly large decreases in late stage diagnosis rates [Kalager et al., 2012, Bleyer and Welch, 2012]. Breast cancer is generally diagnosed by mammograms or self-exams. In a small portion of cases it is diagnosed by doctor administered exams.[3] By definition, mammography, which uses an X-ray image, can detect the tumor when it is smaller and thus is more likely to be an early stage of disease. The question is whether cancers diagnosed earlier would have led to harmful disease or death if they were

[2]Approximate 2009 statistics from the CDC, http://www.cdc.gov/cancer/breast/statistics/ (last accessed 8/2/13).

[3]Personal communication with Judith Malmgren, Department of Epidemiology, University of Washington.

never detected.

The second major critique of general mammography screening is that the number of people needed to be screened is too large relative to the number of lives saved. For example, the USPSTF cited the number of 1904 women needed be invited to mammogram screening per life saved in reversing its recommendation that all women aged 40 to 49 receive regular mammograms [Nelson et al., 2009]. Relatedly, it is argued that the number of false positives is too large relative to the number of lives saved. While the Nelson et al. [2009] study reported results from computer models showing that increasing the age of mammography from 40 to 50 would increase breast cancer mortality by 3% such a change would also be associated with a decrease of 2250 false positives per 10,000 screenings.

This paper considers a policy that will increase the screening rates among women who do not get regular mammograms. That is, women who do not get at least one screening mammogram every two years. Our empirical analysis of the "October" cohort of mammograms suggest that women who are moved to get a mammogram by the advertising blitz are systematically different from women who get mammograms in other months of the year. If this group is disproportionately consists of women who do not get regular mammograms then the effects of a policy that increases screening among these women will have fundamentally different effects than a policy than a policy that increases (or decreases) screening rates for the "average" women.

The policy question is whether changes to incentives to get mammography screening increase survival and are cost-effective. Tabár et al. [2011] consider random assignment of "invitations" among a population that was much less likely to get regular mammograms than the current US population. Kalager et al. [2012] consider quasi-random assignment of screening invitations based on the staggered introduction of county wide programs over a number of years in a population with much lower usage of mammography. Thornton [2008] consider random assignment of actual monetary payments and distance to screening services to determine the impact of changes in HIV screening rates on sexual behavior in Africa. Here we use the advertising blitz associated with NBCAM to identify changes in the likelihood of getting screened and the impact of changes in screening rates on survival.

Although 25% of the study population do not follow the USPSTF guidelines, we do not analyze the "rationality" of this behavior. Oster et al. [2013] presumes the value of screening, and attempts to use behavioral models to understand the limited utilization of the screening. The paper considers the case of Huntington's disease, whose incidence is strongly genetic, and lacks effective treatment, with limited palliative care options. While broadly useful for understanding the advantages and limitations of behavioral (i.e., non-neoclassical) modeling, we focus on a more traditional balancing of costs and benefits. The

debate regarding screening mammograms, and cancer screening more generally, has turned on the possibility of, and value of, early detection. Unlike for Huntington's Disease, early detection may save lives and reduce costs, effects which we aim to measure.

The paper proceeds as follows. Section 2 presents results of the empirical analysis of the relative diagnosis rates, cancer staging and survival of the October cohort of women. Section 3 considers the costs and effects of a policy that increases mammography rates. Section 4 concludes.

2 Data Analysis

We use a 5% Sample of the Medicare population for our study. The Medicare population is, to some degree, a sample of convenience: beneficiary and claims data for individuals on Medicare are made available by CMS. Focusing on this population does mitigate some of the many issues that may be present if we were to study women under 65. Medicare provides universal coverage for women over 65 in the US. If we were to study insured women, we might worry that our estimates were non-representitive due to the endogeneity of private coverage. Also, as the USPSTF guidelines suggest, older women are at a greater risk for breast cancer, while the guidelines for women over 75 have varied over time.

The sample is drawn from all Medicare beneficiaries from 2005-10. The Master Beneficiary Summary File has one observation per beneficiary per year, and includes basic demographic information, including date of birth, sex, race, and monthly entitlement indicators (for Medicare Parts A, B and D). We also have access to the National Death Index (NDI) segment, which states the date of death, so long as it occured during the period of study, 2005-10.

Claims and diagnosis data come from three separate files. First, the Outpatient Claims File collects the claims made by hospital-based outpatient care (Part B) providers. It lists the ICD-9 codes for diagnoses and treatment associated with the visit, as well as the HCPCS (CPT-equivalent procedure code), and APC (bundled payment group), and payment information (who paid and how much). We also have the MedPAR, which reports the ICD-9 codes and bundled payment codes (DRGs) for all inpatient visits to a hospital and skilled-nursing facility. We have the annual measures of spending and visits, by visit type. Importantly, we do not presently have access to the Carrier files, which house the claims for all Part B claims made in a physician practice, or other non-hospital, setting. For example, visits to ambulatory surgical centers or specialty imaging centers are not avaible in the sample we are considering at this time. Because of this, as suggested by McBean [2012], we only have the claims for one-third of the screening mammograms paid for by Medicare. However, we can

measure the annual spending on and number of of those visits by beneficiary-year by using the annual utilization file.

Finally, we use the Chronic Condition Files constructed by CMS. The Condition Files report the conditions (breast cancer, lung cancer, heart disease, etc.), based upon all of the claims sent to CMS. Thus, while we do not have access to the claim associated with a treatment received at ambulatory surgical center, we do know if a beneficiary received such treatment at all, either by July 1st of the year (a semi-annual measure) or by December 31 (the annual measure). It is important to note that this, and all of the diagnoses reported below, rely upon the claims data, and do not reflect the assessment of an independent practitioner. In some instances, diagnosis-by-claim may be unreliable [Taylor Jr et al., 2002]; also, we will be unable to separate "true positives" from "false positives." With those caveats noted, we begin our discussion of mammograms in the Outpatient Claims data.

2.1 Pink October (and November)

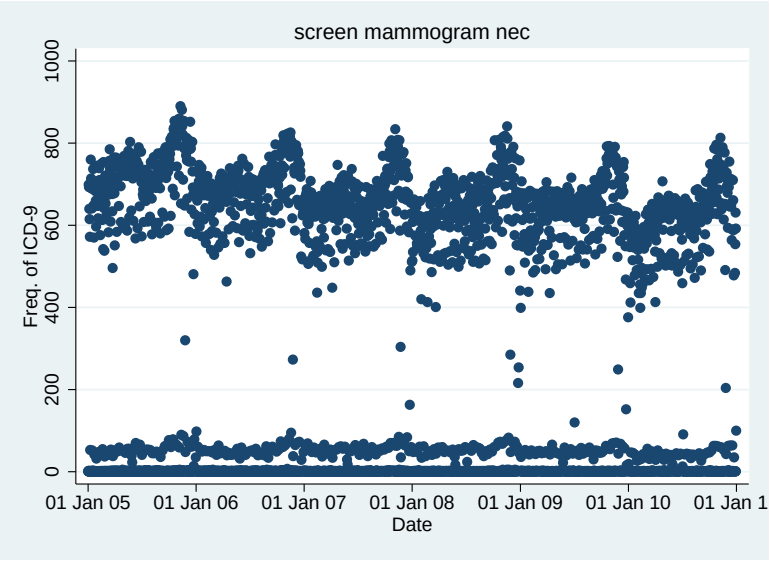
In the Medicare claims data, doctors or other medical professionals code the reason for the visit. In the case of screening mammograms,[4] this corresponds to one of the two procedure codes: V76.12 for ordinary screening mammograms, and V76.11 for screening mammograms of women with risk factors. The records also indicate whether there are other indications for concern, such as an irregularity in the breast or nipple.[5] For either screening mammogram code, women in this sample are not responsible for a co-pay, though they are for diagnostic mammograms.

Figure 1 plots the daily number of screening mammograms from the five percent sample of Medicare, and the seasonality is immediately evident. On the left is the daily count of mammograms without risk factors (V76.12) and the daily count for mammograms with risk factors (V76.11) is on the right. Every fall, October and November in particular, there is an increase in the frequency of screening mammograms. The daily frequency increases, roughly speaking, from an out-of-season average of six-hundred to an in-season peak of over eight-hundred. A similar, if less evident, trend is evident in the mammograms with risk factors, though this trend appear later in the sample.[6] This provides some initial evidence that not only are mammograms seasonal in October and November, but that the mammograms

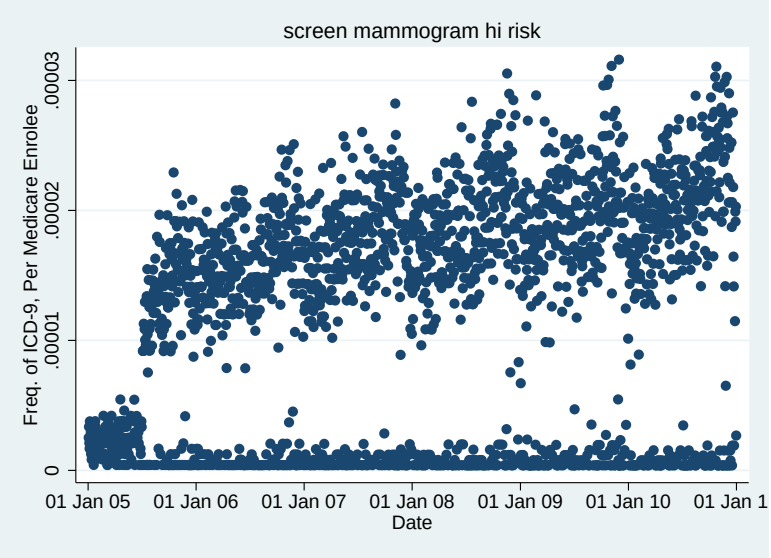
[4]Diagnostic mammograms, which take occur after breast cancer has been diagnosed is coded and reimbursed differently according to Medicare rules. An inspection of diagnostic mammograms, not reported here, does not indicate a similar seasonal pattern.

[5]The data do not appear to systematically differentiate between a high-risk coding and other ICD-9 codes. Ordinary screening mammograms frequently have secondary ICD-9 codes.

[6]There is also evidence of a change in billing practice in early 2005, with the jump in mammograms with risk factors. For reasons besides this, we separate out these two types of mammograms in the results below, and the general trends stand.



(a) Mammograms without risk factors (V76.12)



(b) Mammograms with risk factors (V76.11)

Figure 1: Daily counts of screening mammograms in a hospital-based outpatient setting among 5% Sample Medicare Population, by whether the mammogram is coded with other risk factors.

without risk factors are particularly so. This suggests that mammograms in October and November are more likely to be taken of women less likely to have a strong prior concern for breast cancer. Further evidence of this can be found by separating mammograms with other ICD 9 codes from those without. Such a graph can be found in Figure 2. Again, the seasonality of mammograms is primarily among those mammograms without other (coded) evidence of breast irregularity.

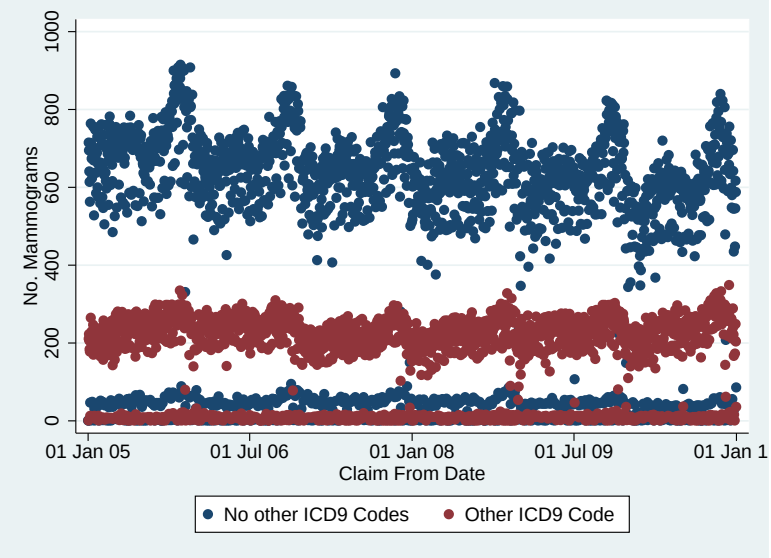


Figure 2: Daily counts of screening mammograms in a hospital-based outpatient setting among 5% Sample Medicare Population, by whether the mammogram is coded with other conditions, such as breast or nipple disfiguration.

2.2 Patterns in Diagnosis and Staging

We investigate the patterns of care and diagnosis associated with mammograms using a 5% sample of Medicare beneficiaries, from 2005-10. The sample draws from the entire population of those eligible and enrolled in Medicare Parts A and B over this six-year period.[7] The sample starts with an annual baseline files, that includes monthly measures of enrollment, race, date of birth and a ZIP+4 code from a billing address. We also have the mortality files, which lists date of death if it occurred in the six year period.

The data present two different ways to discern whether a woman was diagnosed with breast cancer subsequent to a mammogram. The first way uses the Chronic Conditions File, which reports whether a Medicare enrollee's claims data indicate a diagnosis of one of many different diseases, of which breast cancer is one. We can also superficially duplicate this, by reviewing the Outpatient and MedPar (Inpatient and Skilled Nursing Facility) for ICD-9 codes that indicate breast cancer. We limit the matching of breast-cancer related claims to mammograms to be within one year of each other. Both measures have limitations, and so we employ both.

We first consider the Chronic Conditions File. The Chronic Conditions File reports three measures of breast cancer: starting January 1, are there claims suggesting breast cancer by July 1st, by the end of the year, and the date of first diagnosis of breast cancer in the

[7]Enrollees in Medicare Part C (Advantage) HMOs does not have their claims reported into the Medicare claims file, and are thus excluded from the sampling procedure.

patient's medical history, whenever it may have occurred.

The timing of these measures is imperfect for this exercise, as there may be censoring of a diagnosis. E.g., if a women has a mammogram that indicates breast cancer on December 31st, she is unlikely to be coded as having been diagnosed with breast cancer that calendar year. Because the months of interest are sufficiently close to the end of the calendar year, we investigate the potential bias associated with this censoring. First, we measure the difference in diagnosis rates for mammograms that occur near the July 1st condition measure. If those mammograms are not similarly seasonal in their frequency or the risk factors of women who seek mammograms in those months, then such measures should indicate the magnitude of the censoring effects. Second, we look to the July 1st measure of diagnosis of the subsequent year. This limits our sample, as mammograms in 2010 do not have chronic condition indicators for the following July.

We measure the monthly rate of diagnosis using a regression of the following form:

$$D_m = \sum_{8 \leq t \leq 12} I_{m \in t} \beta_t + \epsilon_m, \tag{1}$$

where a unit of observation, m, is a screening mammogram. Because the data is panel, women may have multiple screening mammograms while they are in the data, and we pool over this. The indicators $I_{m \in t} = 1$ when the mammogram took place in a particular month. The coefficients β_t are the different in diagnosis rate, relative to the diagnosis rate in some baseline month or set of months.

Table 1 reports the most generic version of this specification, with separate dummies for each month. The table reports the baseline diagnosis rate (January), and the difference in diagnosis rate for each of the successive months. The diagnosis rate for November is four-tenths of a percentage point less than that of January; this is a ten percent decrease in the diagnosis relative to the baseline, and is statistically significant at the 99 percent confidence level. The other large coefficient is December, which is nearly twice as large and statistically significant, but may suffer from censoring bias. October mammograms appear to be diagnosed at a similar rate to that of January, and the only other months that have coefficients with some statistical significance (May and July) have coefficients half that of November.

The second columns of Table 1 report the point estimates for the same specification, only lagging the date of the mammogram by 14 days. Women who are "induced" to get a mammogram by NBCAM publicity may not get a mammogram that day. Thus, the lag attempts to capture a typical waiting period between when a women attempts to sign up for a mammogram and ultimately has one. The difference between the diagnosis rates of

Table 1: Month-of-mammogram Diagnosis Rate Patterns

January	0.0436***		July	0.00207**	0.00118
	(0.000637)			(0.000907)	(0.000889)
February	0.000679	0.000172	August	-0.000470	-0.000687
	(0.000927)	(0.000917)		(0.000878)	(0.000878)
March	0.000403	0.000784	September	-0.00108	-0.000413
	(0.000888)	(0.000885)		(0.000880)	(0.000863)
April	0.000432	0.00181**	October	-0.000191	-0.00188**
	(0.000891)	(0.000891)		(0.000851)	(0.000835)
May	0.00200**	0.00105	November	-0.00356***	-0.00525***
	(0.000897)	(0.000889)		(0.000851)	(0.000847)
June	0.00133	0.00139	December	-0.00782***	-0.00455***
	(0.000888)	(0.000901)		(0.000847)	(0.000886)
14-day lag		Yes			Yes
		N=1,323,605			

Note: Estimates for linear probability models of (relative to January) monthly diagnosis rates, with robust standard errors in parentheses. Each point estimate reflects the average diagnosis rates for women subsequent to mammograms by month, relative to those in January. The first column uses the actual date of the mammogram to determine the monthly averages, while the second column uses the month of the date of the mammogram plus fourteen days.
* significant at 10%; ** significant at 5%; *** significant at 1%.

October and January is now statistically significant, while the November and December diagnosis rates remain smaller than those in January. Thus, the second half of October, when combined with the first half of November, appears to have a lower diagnosis rate than January. The May drop in diagnosis rate appears to be an early-May pattern, as the late-April/early-May coefficient is also statistically significant at the 95% confidence level. The July pattern disappears.

In order to maximize the power of the analysis, we group January through September into a rest-of-year (ROY) average, and use that as the baseline. Table 2 uses the ROY baseline to measure the extent to which the end-of-year measures of diagnosis may be influencing the estimates. As mentioned before, the diagnosis measures used here rely upon claims made by December 31st. If a woman has a mammogram on December 30th, is diagnosed with breast cancer, and her treatment starts January 1st, she will still be recorded as undiagnosed in the measure used here. The first, third and fifth columns repeat use the end-of-year diagnosis variable, and the monthly diagnosis rates relative to the pre-October (ROY) average. The patterns here are consistent with the specifications when all months are allowed their own separate dummy variable.

Table 2: Alternative specifications for Diagnosis Rate Patterns

	End of Year	By Next July 1	End of Year	By Next July 1	End of Year	By Next July 1
ROY	0.0442***	0.0579***	0.0232***	0.0322***	0.0319***	0.0429***
	(0.000209)	(0.000258)	(0.000178)	(0.000226)	(0.000184)	(0.000230)
October	-0.000778	-0.00195***	-0.00140***	-0.00309***	-0.00207***	-0.00351***
	(0.000602)	(0.000737)	(0.000501)	(0.000626)	(0.000519)	(0.000644)
November	-0.00415***	-0.00364***	-0.00252***	-0.00221***	-0.00469***	-0.00450***
	(0.000602)	(0.000756)	(0.000505)	(0.000656)	(0.000517)	(0.000661)
December	-0.00840***	-0.00606***	-0.00524***	-0.00435***	-0.00792***	-0.00592***
	(0.000597)	(0.000772)	(0.000494)	(0.000661)	(0.000509)	(0.000677)
	1,323,605	1,125,746	988,014	841,533	1,254,045	1,066,951
ICD 9			No	No		
Risk factors					No	No

	Diagnosed by July 1				
January	0.0429***	0.0432***	April	0.000982	0.00134
	(0.000632)	(0.000527)		(0.000888)	(0.000815)
February	0.000698	-0.000296	May	0.000452	-0.00274***
	(0.000920)	(0.000842)		(0.000883)	(0.000795)
March	0.000252	0.000759	June	-0.00422***	-0.00511***
	(0.000881)	(0.000810)		(0.000856)	(0.000942)
	634,724	634,724		634,724	634,724
14-day lag		Yes			Yes

Note: Estimates for linear probability models of (relative) monthly diagnosis rates, with robust standard errors in parentheses. Each column in the top panel reports the diagnosis rates for mammograms in October, November, and December, relative to those in the rest of the year (ROY). The different columns, consecutively, report the point estimates for different alternative measures of diagnosis, and whether the result is statistically significantly different from zero. The bottom panel reports the rates of diagnosis by the month of the mammogram, using the measure of diagnosis using claims dated before July 1st. The first column uses the actual date of the mammogram, while the second column uses the month of the date of the mammogram plus fourteen days.
* significant at 10%; ** significant at 5%; *** significant at 1%.

The accompanying second, fourth and fifth columns update the diagnosis measure, setting it equal to one if the beneficiary has claims that suggest diagnosis by the following July. Because this uses claims from a subsequent year, mammograms from 2010 are dropped and the sample falls by roughly one-sixth. As reported in the first and second columns, the baseline diagnosis rate grows from four and half to over five and half percent, as more time is allowed pass for diagnosis to occur. The October coefficient doubles in magnitude, to a three percent decrease from the baseline, while the November point estimate falls slightly. The December coefficient falls by a third. This suggests that the broader measure of diagnosis mitigates the end-of-year censoring, while allowing increasing the difference between October

and pre-October months.

The final four columns in the top half of Table 2 consider the differences in diagnosis rates for screening mammograms that (a) are coded as necessary, but not for high-risk women, and (b) did not have an second ICD-9 diagnosis code recorded. As described above, these are the mammogram types that demonstrate the most growth in frequency in October and November. The point estimates suggest that, for these low-risk groups, the difference in diagnosis is larger for women with fewer secondary diagnostic concerns. First, note that the diagnosis rate is less for these groups than all screening mammograms, falling from a third (non-high-risk mammograms) to a half (no other ICD-9 codes). Thus, it seems reasonable to conclude that these mammograms are for lower-risk women, all year long.

For these lower-risk women, these diagnosis difference in October, November and December are more pronounced. While the level of the point estimate is smaller in these smaller groups, it is relative to a smaller baseline. In terms of the underlying diagnosis rate, these patterns reflect larger percentage differences than for the entire sample. Across the two diagnostic measures, the decrease in diagnosis rate in the last three months is five to ten percent of the baseline rate, and is statistically significant at the 99% confidence level.

Table 2 also reports the monthly diagnosis rates for the first six months, relative to January, using the mid-year diagnosis measure. To the extent that selection into screening mammograms in those six months is relatively homogeneous, the diagnosis rates for the last two months might also be used to proxy for the amount of non-diagnosis due to censoring. The difference in diagnosis by July 1st appears to be limited to June mammograms, May if the fourteen-day lag is included. The magnitude of the June difference suggests that the December, though not October or November, differences may due to censoring, in no small part. However, the differences due to October should not be of concern.

2.3 Staging and Mortality

In spite of this fall in the diagnosis rate, increased efforts to find and diagnose cancer may still be worthwhile. Cancer is generally segmented into three basic categories: metastatic, regional and local.[8] A "late stage" diagnosis is given to metastatic disease. This is the case where the cancer has spread from the initial location in the breast to other organs and parts of the body. In many cases metastatic cancer is not curable with current technology. It is usually not possible to remove all the tumors with surgery. Radiation may reduce the size of the tumors but it often does not remove them completely and it often does significant damage to the surrounding tissue. Chemotherapy can stabilize the growth and spread of the

[8]See the National Comprehensive Cancer Guidelines on breast cancer at http://www.nccn.org.

tumors but often cannot hold back the spread indefinitely. In the model of the Medicare population presented below, 53% of Stage 4 patients are alive after five years.

Regional or invasive cancers have not yet spread to other distant organs but may have spread to nearby cells or into the lymphatic system. Regional cancers are not life threatening but left untreated they have a high likelihood of spreading to other organs, leading to death. Regional cancers are usually operable and patients often undergo radiation and chemotherapy regime because there is evidence that these treatments significantly reduce the likelihood that the cancer will spread. Patients with a regional diagnosis are usually followed for a number of years after they have completed the surgery, radiation and chemotherapy. They are generally considered to be "cured" if the cancer has not been found to have spread after five years from surgery. Patients with regional cancers are relatively expensive to treat particularly if they are given the new drug regimes. In the model of the Medicare population presented below the expected net present value of Medicare and out-of-pocket expenses for such a patient over the next 5 years is $105,438. According to the model, 92% of such patients are alive after five years.

Patients for whom the tumor has yet to invade nearby tissue or the lymphatic system are diagnosed with early or local stage cancer. These patients may also get surgery and in rarer cases may get radiation and chemotherapy. Given the reduced treatment it follows that these patients are relatively inexpensive to treat.

The public health objective of a cancer screening program is to diagnose patients before the cancer spreads to distant organs. If a screening program can successful diagnose patients with earlier stages of cancer those patients may be treated and there is a significant probability that their life will be saved. The economic benefits of a general screening program may include the economic value of the life-years saved as well as the medical expenditure savings. The costs of the a general screening program includes the costs associated with the screening themselves as well as the costs of the associated follow up tests and treatments. The test technology may also be inconvenient and involve personal costs to those screened.

The viability of such a claim relies on the ability of increased detection to lead to early detection, and that early detection to lead to decreased mortality (among other things). The data allow us the ability to test such claims directly. Using the ICD-9 disease codes in the hospital-based outpatient and inpatient claims data, we are able to code each visit as associated with four separate stages of breast cancer: Stage 0 (233.0), Stage 1 (174) Stages 2 and 3 (174 and 196), and Stage 4 (174 and either 197 or 198). We match each screening mammogram to the twelve months of claims that are coded as being related to breast cancer.[9]

[9]Our measurement of diagnosis may vary from Medicare's measurement of diagnosis for a variety of

Table 3: Differences in Diagnosis and Cancer Staging by Month of Mammogram

	EOY DIAGNOSIS			Stage 2,3 or 4		
ROY	0.0442***	0.0232***	0.0319***	0.0835***	0.0928***	0.0886***
	(0.000209)	(0.000178)	(0.000184)	(0.00198)	(0.00318)	(0.00233)
October	-0.000778	-0.00140***	-0.00207***	-0.00321	0.00456	0.00245
	(0.000602)	(0.000501)	(0.000519)	(0.00565)	(0.00938)	(0.00688)
November	-0.00415***	-0.00252***	-0.00469***	-0.00716	-0.00668	-0.00498
	(0.000602)	(0.000505)	(0.000517)	(0.00589)	(0.00934)	(0.00706)
December	-0.00840***	-0.00524***	-0.00792***	-0.00118	-0.00167	-0.00333
	(0.000597)	(0.000494)	(0.000509)	(0.00645)	(0.0102)	(0.00757)
Sample	1,323,605	988,014	1,254,045	26,394	11,350	20,042
ICD 9		No			No	
Risk factors			No			No
	Initially Stage 0			Stayed at Stage 0		
ROY	0.152***	0.179***	0.173***	0.0403***	0.0468***	0.0418***
	(0.00257)	(0.00420)	(0.00311)	(0.00141)	(0.00231)	(0.00164)
October	-0.0114	-0.00427	-0.00464	-0.00203	-0.00339	0.00163
	(0.00724)	(0.0120)	(0.00897)	(0.00399)	(0.00649)	(0.00487)
November	0.0113	0.0318**	0.0226**	0.00552	0.00902	0.00864
	(0.00814)	(0.0134)	(0.0100)	(0.00459)	(0.00754)	(0.00553)
December	0.00677	-0.00321	0.0148	0.000626	-0.00803	0.00342
	(0.00856)	(0.0135)	(0.0105)	(0.00464)	(0.00691)	(0.00561)
Sample	26,394	11,350	20,042	26,394	11,350	20,042
ICD 9		No			No	
Risk factors			No			No

Note: Estimates for linear probability models of (relative) monthly diagnosis rates and cancer staging, with robust standard errors in parentheses. Each point estimate reflects the average mortality rates for women subsequent to mammograms in October, November, and December, relative to those in the rest of the year (ROY). The panels report the point estimates for four different measures of diagnosis and staging, according to outpatient and inpatient claims submitted to Medicare within one year of the mammogram. Each column reports the point estimates by subgroups of women. The second and fifth columns exclude those women whose doctors indicated that she had risk factors, such as family history, at the time of the mammogram. The third and sixth columns exclude mammograms that had indicated other medical diagnoses, as indicated by the ICD 9 codes on the screening mammogram's claim.

* significant at 10%; ** significant at 5%; *** significant at 1%.

reasons, included but not limited to: our lack of Carrier-based claims, different code patterns used to recognize breast cancer-related care, and diagnosis during a calendar year (the Chronic Condition File) vs.

Table 3 reports the rates of these associated outcomes, by month of mammogram. The results for diagnosis can be found in Panel A. The three columns represent specifications for the entire sample of mammograms, those mammograms with no other ICD-9 codes, and those mammograms coded as necessary but not high risk. Our measurement of diagnosis is about two-thirds that of CMS's measure, and the corresponding monthly differences in diagnosis is also smaller. The sample here is also smaller, as the mammograms from 2010 do not have full year of the follow-up care in our data.

Panel B reports the monthly differences in the rates of Stage 2 or higher breast cancer. Stage 2 or higher breast cancers have initially spread, and are associated with higher mortality rates (see discussion above). At this point, the sample diminishes quickly, as the cancer rate among women in these groups is below five percent, leaving just over 28,000 women in the sample of women who had a mammogram in a hospital-based outpatient clinic and also received treatment associated with breast cancer. The point estimates reported in Panel B are all small in absolute terms: the largest difference in the rate of Stage 2 or higher breast cancer is seven-tenths of one percent, and is not even ten percent of the eight-percent baseline risk of that group. The balance of the point estimates are typically smaller, either within the group as a whole, or among the women without other risk factors suggested in their mammogram claim. None of the point estimates are statistically significantly different from zero at traditional levels.

As mentioned above, much of the debate around mammogram use centers around earlier stages. Panels C and D report the incidence of Stage 0 breast cancer claims, by month of screening mammogram. The outcome of interest for Panel C is whether there were any codings for Stage 0 breast cancer; for Panel D, the outcome of interest is whether Stage 0 was the only coding for subsequent breast cancer treatment. The results suggest that there is a peak in some Stage 0 treatment following a November mammogram, particularly among lower-risk women. However, these point estimates do fall when the outcome is exclusively Stage 0 breast cancer. The baseline risk of exclusively Stage 0 relative to any Stage 0 is roughly proportional to the relative size of the point estimates, and are not statistically significant at the usual confidence levels. The sample is small, so the analysis lacks power to precisely estimate a difference. That said, we do not find strong evidence that these NBCAM-timed mammograms move staging up in any consistent way.

Finally, we consider the mortality rates of women who get mammograms, using the date of death available in our data. We calculate the one-, two-, and three-year mortality rates. The sample for these latter two measures shrink, as we lose the later years in our

a rolling year-long window (our measure).

Table 4: Differences in Mortality Rates by Month of Mammogram

	Mortality Rates—All			Mortality Rates—Diagnosed		
	1 Year	2 year	3 year	1 Year	2 year	3 year
ROY	0.0130***	0.0264***	0.0378***	0.0283***	0.0570***	0.0774***
	(0.000140)	(0.000227)	(0.000327)	(0.000996)	(0.00160)	(0.00226)
October	-0.000549	-0.00159**	-0.00136	-0.00495*	-0.00837*	-0.00928
	(0.000398)	(0.000644)	(0.000951)	(0.00267)	(0.00441)	(0.00635)
November	-0.000338	-0.000450	-0.000338	-0.00456	-0.0104**	-0.00971
	(0.000415)	(0.000670)	(0.000970)	(0.00294)	(0.00466)	(0.00683)
December	-0.00187***	-0.00189***	-0.00282***	-0.000562	0.000947	0.00539
	(0.000410)	(0.000694)	(0.000993)	(0.00340)	(0.00564)	(0.00803)
Sample	899,725	684,251	464,701	37,032	27,775	18,645

Note: Estimates for linear probability models of (relative) mortality rates, with robust standard errors in parentheses. Each point estimate reflects the average mortality rates for women subsequent to mammograms in October, November, and December, relative to those in the rest of the year (ROY). Panel A reports the point estimates for entire sample, while Panel B reports the point estimates for the subsample of women who were diagnosed with breast cancer during the calendar year of their mammogram. Each column reports the (relative) rates by subgroups of women defined by the risk factors at the time of the mammogram, as described by the medical diagnosis codes in the screening mammogram's claim.

* significant at 10%; ** significant at 5%; *** significant at 1%.

sample.[10] As is standard in the cancer survival literature, we consider mortality due to any reason. The differences by month of mammogram are available in Table 4, and is presented for either all women or conditional on (CMS's) diagnosis of breast cancer that calendar year. As with the staging analysis, there is limited evidence that the increase in (low-risk) screening associated with October and November mammograms is associated with decreased mortality. Conditional on having been diagnosed, there is a decrease in one- and two-year mortality on the order of fifteen to twenty-percent of the baseline mortality risk for October mammograms; this difference is statistically significant at the 90 percent confidence level. There are similar differences for November, though all of these differences tail off, both in terms of size relative to the rest-of-year mortality and statistical significance, for the three-year mortality measures. Not surprisingly, when the sample is not conditioned on by diagnosis with breast cancer, the monthly differences shrink.

The empirical analysis shows that the October cohort of mammograms is associated with women who have a lower risk of breast cancer, who are less likely to have breast cancer and who are somewhat more likely to be diagnosed with Stage 0 breast cancer conditional upon diagnosis. There is no direct evidence that the October cohort is associated with greater survival rates.

3 Policy Analysis

The previous section empirically analyzed the relationship between having a mammogram during "Pink October" with breast cancer diagnosis, with the initial staging conditional upon diagnosis and with survival conditional on diagnosis and unconditionally. The analysis did not distinguish between women whose regular mammogram happened to be during Pink October and women induced to have a mammogram by Pink October. The analysis was also limited by the length of the panel. This section attempts to compensate for these issues using a structural model to identify the women at risk of being induced to have mammograms by some policy intervention and a statistical model that allows more efficient use of the data in measuring survival rates and policy costs.

Consider a woman who has breast cancer, but does not know it. She has two ways to discover that she has breast cancer: she can have a screening mammogram, or she can self-diagnose via a physical examination. When cancer is discovered via either of these methods, she enters treatment at a particular stage, which is associated with increases in medical spending (both out-of-pocket and Medicare), mortality, and transition to subsequent stages of cancer (which are themselves also associated with different levels of medical spending and

[10] Date of death is only available if the death occurred during our sample period, 2005-10.

mortality.)

We assume that some proportion of the population get regular screening mammograms at least once every two years, while the remainder do not get mammograms or do not get screening mammograms on the recommended schedule. The policy intervention of NBCAM does nothing for this first group, as they would have had a mammogram anyway. The intervention on the second group induces them to have a mammogram when they would not have, or would have had a lower probability of screening.[11]

The appendix presents conditions under which the observed increase in mammograms associated with NBCAM identifies the initial staging distribution for these women who are induced by NBCAM, conditional upon getting a mammogram and being diagnosed with breast cancer. It also presents additional assumptions required to identify the initial staging distribution for these women conditional upon being self-diagnosed with breast cancer. In short, these assumptions are similar to the ones required to generalize a random-controlled experiment into a two-type model that we use here. While we our research design does not satisfy the exogeneity assumptions of such "gold standard" designs, identification of an underlying model requires similar assumptions in both cases.

Stage	All	Oct	Aug	Induced	Self
0	0.043	0.043	0.041	0.051	0.049
1	0.823	0.880	0.880	0.877	0.649
2.3	0.059	0.035	0.036	0.032	0.130
4	0.075	0.042	0.043	0.040	0.172

Table 5: Actual and Inferred Initial Stage Probabilities

Table 5 presents the distribution of initial staging by various classes of diagnoses. The first three columns are just read from the data. The first column is the distribution for women diagnosed with breast cancer irrespective of the method used to diagnose. The second column is the distribution for mammograms that occurred in the second half of October and the first half of November. The third column is the distribution for mammograms that occurred in the second half of the year but not Pink October. The last two columns come from the data based on equations and assumptions presented in the appendix. The fourth column comes from Assumption 6 which states that the initial staging distribution is a function of the "Oct" and "Aug" columns with a weight related to the 25% increase in mammograms associated with Pink October. The fifth column is the initial staging distribution for women

[11]There is ostensibly a third group, women who do not have a mammogram whether or not NBCAM exists. Because we are working from the set of women who have mammograms, we are not able to assess the value of ensuring that they get mammograms.

that are self-diagnosed. It is a weighted function of the first three columns where the weight is determined by proportion of women who got a mammogram in the current period (see Equation 18).

Note that the assumption that all of the "extra" peak month mammograms are for women who otherwise would not get a regular mammogram minimizes the measured difference between them and the ordinary mammograms that would have occured in October (or some other month) absent NBCAM. In extremis, were we to assume that only one woman was induced by NBCAM, then we would ascribe all of the difference between the October and August (or rest-of-year) to her. This one woman would have an exaggerated diagnosis and staging profile. By going to the other extreme, we are setting up the induced mammograms to be as similar as possible to the mammograms that would have occured anyway, providing a upper bound for how cost-effective the induced mammogram may be.

Table 5 shows that women who are induced to have mammograms are significantly down-staged relative to women who are self-diagnosed with breast cancer. Consistent with the results presented above, the initial staging distribution for the "Oct" mammograms is similar to that of the "Aug" mammograms. However, the structural model assumes that the small observed difference is driven by the additional mammograms seen in October, all of whom are given to women who do not receive regular mammograms. The women who are induced to have a mammogram by Pink October have a one percentage point higher probability of being diagnosed with Stage 0 relative to women who have mammograms in an "average" month. The women who are self-diagnosed are significantly more likely to have the higher stages of breast cancer than those diagnosed through mammograms. This difference comes from the fact that the staging distribution unconditional on screening is weighted somewhat to the higher stages and the fact that only 25% of women did not have a mammogram in the last two-years.

Stage (T-1,T)	0	1	2.3	4	Pr(death)
0	0.878	0.118	0.001	0.003	0.007
1	0.000	0.982	0.004	0.014	0.013
2.3	0.000	0.000	0.954	0.046	0.013
4	0.000	0.000	0.000	1.000	0.148

Table 6: Transition Probabilities

We presume that inducing a screening mammogram helps the woman with cancer by catching the cancer earlier. Vis-a-vis self-diagnosis, a cancer caught by a screening mammogram may be caught at an earlier stage because the mammogram can detect a smaller collection of cancer cells than the human hand can detect. The tables above demonstrate

that this is true.

We also presume that increased utilization of screening mammograms is costly both to the woman and to Medicare by catching cancer earlier; i.e., starting the spending on cancer treatment at an earlier point in time than if the woman had delayed her screening mammogram by a year, or instead relied upon self-diagnosis. The net value of an induced mammogram compares the benefits of diagnosing a cancer earlier (earlier staging leading to lower mortality and less post-diagnosis spending) to its costs (starting the spending earlier than it otherwise would have). These costs and benefits crucially depend upon the transition probabilities and spending associated with different stages of cancer.

Table 6 presents the transition probabilities between the various states in the Markov model. There are six states in the model, Stage 0, Stage 1, Stage 2/3, Stage 4, Year of Death, and Passed Away. For each year, the patient is assigned the "highest" stage of the disease diagnosed in that calendar year. Note that the year of death is considered as a separate state because it is associated with large medical expenses. Patients who passed away in the previous year are assumed to have no medical expenses in the current year.

The first four columns of Table 6 present the probability of moving from one stage of disease to another conditional on not dying within the year. The fifth column presents the probability of dying within the year conditional on the stage of disease. Note that by assumption the women only move "up". For women diagnosed Stage 0, there is a 10% probability that they will be diagnosed with invasive breast cancer within the year. Women diagnosed with Stage 1 breast cancer have less than a 2% probability of being diagnosed with higher stage or passing away within 12 months. Women diagnosed with Stage 2 or 3 breast cancer have a 5% probability of having the cancer metastasize within the year. Women with Stage 4 have a 15% probability of passing away within the year. Note that these transition probabilities are assumed to be the same for each woman irrespective of the technology used to diagnose breast cancer.[12]

Table 7 presents survival probabilities which are calculated by running the transition probabilities (Table 6) through four iterations. The table shows that the 5-year survival probability is relatively high for women staged between 0 and 3, but significantly lower for women with metastatic disease.

The table also presents the survival probabilities for various demographic subsets of the data including by age, race and ethnicity. We separate women above (and below) 75 years of age, corresponding to the cut-off suggested by the USPSTF, ostensibly informed by varying levels of underlying health associated with age. As suggested by Card et al. [2008], there is reason to believe that socioeconomic differences in insurance coverage prior to entering

[12]We do consider transition probabilities by demographic characteristics.

	Initial Stage			
	0	1	2.3	4
All	0.97	0.94	0.92	0.53
75+	0.95	0.92	0.90	0.49
<75	0.98	0.96	0.93	0.56
White	0.96	0.94	0.92	0.51
Black	0.95	0.92	0.85	0.43
Hispanic	0.99	0.94	0.92	0.52

Table 7: Five Year Survival by Initial Stage

Medicare at age 65 have lasting consequences for the quantity and composition of care received by those groups. The underlying causes for the different results by demographic group may only superficially be related to the demographics we consider. However, they do suggest how robust the cost-benefit analysis we conduct is to the kinds of variation one does see within the general population of elderly women.

We calculate the stage transition and mortality probabilities, as well as medical spending patterns described below, separately by demographic characteristics. In contrast, because the number of first-time cancer diagnoses is small, the initial staging is constant across demographic characteristics. There is not much variation in survival among the different demographic subgroups. As expected younger women have higher 5-year survival than older women. African-American women diagnosed with breast cancer have lower 5-year survival than white or Hispanic women.

	Induced	Not Induced	Difference
All	0.924	0.905	0.019
75+	0.906	0.888	0.018
<75	0.942	0.921	0.021
White	0.921	0.901	0.020
Black	0.901	0.877	0.024
Hispanic	0.929	0.908	0.021

Table 8: Five Year Survival Probabilities (Type 2)

Table 8 presents five year survival rates among women with breast cancer who do not receive regular mammograms (type 2 women). The first column is for the women that get a mammogram in the current period. Their survival probability is calculated by taking their initial staging distribution (fourth column of Table 5) and running the Markov process through using the transition probabilities for each demographic group (not presented).

Calculating the survival probability for women with breast cancer who don't receive regular mammograms and who didn't receive a mammogram in the current period is more challenging. Such women may or may not be diagnosed with breast cancer and if they are diagnosed it could either be through self-diagnosis or through a screening mammogram. So as discussed in the appendix we need to determine the probability of a screening mammogram for a type 2 woman with breast cancer, the probability of self-diagnosis given the women has breast cancer and the probability of a women with breast cancer dieing without being diagnosed.

In regards to the first probability, we know that 75% of women have had a mammogram in the last two years. We assume that 100% of type 1 women have had a mammogram in the last two years. If we knew the probability that a type 2 women has a mammogram in a two year period, then we could also determine the proportion of type 2 women in the population. While the data provides information on mammogram usage for a large group of women over a six year period, our sample is limited to mammograms provided in the hospital setting. We limit our analysis to women who received at least one screening mammogram in the hospital setting over the six year period, and calculate the proportion of women who had less than one mammogram every two years. 51% of these women were observed having less than the recommended number of mammograms over the six year period.[13] By Equation (16), the probability that a type 2 women has a mammogram in a two year period is also 51%. Note that if a women with breast cancer has a mammogram in the future, they are assumed to be diagnosed with breast cancer 100% of the time.

A women with breast cancer may also be diagnosed through self-exam. To calculate the probability of a women with breast cancer diagnosing herself, the paper compares this distribution to the underlying staging distribution which is assumed to be equal to the initial staging distribution of women induced to have a mammogram. In addition, it is assumed that a women with Stage 4 breast cancer will self-diagnose with certainty within the year. The appendix presents the details of the methodology used.

The third possibility is that the women passes away prior to be diagnosed. Unfortunately, we don't observe the probability of surviving to the next year for women with breast cancer who remain undiagnosed. It is assumed that the 12 month survival probability for a women with breast cancer who is undiagnosed is that same as the 12 month survival probability for a women induced to have a mammogram by Pink October and who is then diagnosed with

[13]The proportion of women who do not receive regular mammograms may be higher if these women are included in the group who received 3 or more mammograms in the six year period. It may also be lower, because some of the women for whom we do not observe a mammogram, may be getting their regular mammogram outside of the hospital setting. This, even though these women got at least one mammogram in the hospital setting.

breast cancer.

If a women is diagnosed with breast cancer at a later date then their initial staging distribution will depend on how they were diagnosed. If they were diagnosed through a screening mammogram then they are assumed to have the same initial distribution as the average women who receives a screening mammogram in the calendar year. This distribution is given by Table 5, where columns "Oct" and "Aug" are weighted by $\frac{1}{12}$ and $\frac{11}{12}$ respectively. Note that this initial staging is slightly upstaged from the staging distribution of women induced to have a mammogram by Pink October. If a women is self-diagnosed then her initial staging distribution is given by the "Self" column of the same table. These women are upstaged relative to women diagnosed through a screening mammogram.

The results show that given the assumptions, women with breast cancer induced to have a mammogram have a 2 percentage point increase in five year survival compared to women with breast cancer who were not otherwise induced to get a mammogram. The results also show that the effect is larger for women under 75 than it is for younger women, and it is larger for African-American women.

Inducing women who do not receive regular mammograms to have a mammogram increases survival. This occurs because women with breast cancer who are detected through mammograms have their initial staging distribution down-shifted relative to the same women who are eventually self-diagnosed.

	Initial Stage			
	0	1	2.3	4
All	62,936	69,796	105,438	136,633
75+	67,078	71,667	93,396	120,343
<75	59,524	68,646	115,406	153,901
White	62,499	68,255	101,132	130,379
Black	78,590	86,102	126,787	142,392
Hispanic	62,605	79,812	102,225	138,040

Table 9: Five Year Expected NPV of Total Expenditure ($) by Initial Stage

Table 9 presents the net expected present value over 5 years of Medicare and patient expenditure for patients diagnosed with the various stages of breast cancer. The value is calculated assuming a discount rate of 95% and using the transition and survival probabilities presented above in conjunction with the average annual expenditure on patients in each of the six states of the Markov process. The table shows that medical expenses for a women diagnosed with Stage 0 breast cancer will expect to be around $62,000 over the next five years after diagnosis. The expense is slightly higher for Stage 1 women. For a women diagnosed

with breast cancer that has metastasized to her lymphatic system, the medical costs over the next 5 years are expected to be a little over $105,000. If the cancer has metastasized to distant organs the expected medical expenses increases to $136,000. Note that Stage 4 patients are expensive to treat, and are also more likely to pass away. African-American women have both lower survival by stage and higher expected expenses by stage.

	Induced	Not Induced	Difference
All	73,268	72,320	948
75+	74,080	72,333	1,747
<75	73,099	72,721	378
White	71,506	70,367	1,139
Black	89,282	86,641	2,641
Hispanic	81,989	77,165	4,823

Table 10: Five Year Expected NPV of Total Expenditures ($) (Type 2)

Table 10 presents the difference in total expected medical expenditure over 5 years for women with breast cancer who are induced to have mammograms by Pink October and those who are not. The first column is the expected 5-year total expenditure for women with breast cancer who are induced to have a mammogram by the various demographic categories. Columns 2 and 3 present the expenditures for women with breast cancer who were not induced to have a mammogram and the difference between them. These results are presented under the assumption that for these women the probability of dying within the year is the same as for women induced to have a mammogram who are diagnosed with breast cancer.

In order to determine the cost effectiveness of an intervention that induces women with breast cancer to get mammograms the paper compares the increase in survival to the increase in total expenditures associated with inducing mammograms. Using the numbers from Table 8 the 5-year annualized survival difference 0.0041. That is, mammography increases the annual probability of survival by approximately 0.4 of a percentage point. If the annual value of a life is assumed to be $47,000 then the annual increased benefit of mammography $190, which is the same as the average increase in expected net present value of expenditures over 5 years.

4 Conclusion

National Breast Cancer Awareness Month is the preeminent public health awareness campaign. As we demonstrate, it coincides with a twenty-five percent spike in mammograms in

the Medicare population. The women induced to have mammograms by NBCAM are less likely to have breast cancer than women who get mammograms at other times of the year. They are also somewhat more likely to be diagnosed with Stage 0 breast cancer. In addition this cohort of women has similar one, two and three year survival as the cohort of women who have mammograms at other times of the year.

The paper uses the empirically observed increase in mammography associated with NBCAM to identify the impact of a policy that would induce a mammogram among women who would never otherwise have one. A women with breast cancer who is induced to have a mammogram has a two percentage point increase in five-year survival relative to the case where she was not induced to get a mammogram. This increase in survival is associated with a $1,000 increase in total expected medical expenditures. Such a policy is cost-effective under the assumption that the value of a human life year is greater than $47,000 and the costs of mammography to the undiagnosed is zero.

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5 Appendix: A Model of Selection into Diagnostic Screening

This appendix presents a model of mammogram screening participation and presents assumptions sufficient to identify the impact of a policy that increases screening rates, given the data available. There are three results. First, the appendix shows that any policy will increase survival if and only if women with breast cancer who do not receive regular mammograms have greater survival rates if they receive a mammogram in a particular period than if they do not. Second, reasonable assumptions allow the survival probability of these women to be measured when they get a mammogram in a particular period. Third, the survival probability of these women is identified up to a range of values when they do not receive a mammogram in a particular period. That is, the data and the assumptions of the model presented below allow the survival effect of a policy to increase screening rates is identified up to a range of values.

Consider a world in which there are two types of women $\{\theta_1, \theta_2\}$. Type 1 women get regular mammograms. They follow the recommendation of the USPSTF and have a mammogram every two years. Type 2 women do not receive regular mammograms. Type 2 women receive mammograms at irregular intervals that may be more than 2 years apart.

$$\begin{aligned} \Pr(m_{ti} = 1 | \theta_i = \theta_1) &= 1 \\ \Pr(m_{ti} = 1 | \theta_i = \theta_2) &= p < 1 \end{aligned} \tag{2}$$

where $m_{ti} \in \{0, 1\}$ denotes whether women i has a mammogram within the two-year time period t.

Let $\sigma \in \{0, 1\}$ denote a policy intervention that increases the probability a particular women i has a mammogram in period t.

$$\Pr(m_{ti} = 1 | \theta_i = \theta_2, \sigma = 0) = p < \Pr(m_{ti} = 1 | \theta_i = \theta_2, \sigma = 1) = p_\sigma \tag{3}$$

Such a policy (σ) may be an awareness campaign like NABCM or the CDC's National Breast and Cervical Cancer Early Detection Program.

The most obvious benefit of such a policy is that it has the potential to increase survival.

$$\Pr(\tilde{t}_i > T | \theta_i = \theta_2, \sigma = 1) - Pr(\tilde{t}_i > T | \theta_i = \theta_2, \sigma = 0) \tag{4}$$

where $\tilde{t}_i$ represents the year of death of women i.

Before looking more closely at this difference, consider the following two assumptions. The first assumption states that the probability of having breast cancer is independent of the policy. Note that this is the probability of actually having breast cancer rather than the probability of having the breast cancer detected. The second assumption states that conditional on not having breast cancer, the survival probability is not affected by the policy.

Assumption 1.

$$\Pr(BC_i = 1 | \sigma = 1) = \Pr(BC_i = 1 | \sigma = 0) \tag{5}$$

where $BC \in \{0, 1\}$ indicates whether the women has breast cancer.

Assumption 2.

$$\Pr(\tilde{t}_i > T | \sigma = 1, BC_i = 0) = \Pr(\tilde{t}_i > T | \sigma = 0, BC_i = 0) \tag{6}$$

Given these two assumptions we can write the difference as

$$\begin{gathered}\Pr(\tilde{t}_i > T|\theta_2, \sigma = 1) - Pr(\tilde{t}_i > T|\theta_2, \sigma = 0) \\ = \\ \Pr(BC_i = 1|\theta_2)(\Pr(\tilde{t}_i > T|\theta_2, \sigma = 1, BC_i = 1) - \Pr(\tilde{t}_i > T|\theta_2, \sigma = 0, BC_i = 1))\end{gathered} \tag{7}$$

Note that we can expand out the survival probability for the patient's with breast cancer into a group that receives a mammogram and a group that does not receive a mammogram.

$$\begin{aligned}\Pr(\tilde{t}_i > T|\theta_2, \sigma, BC_i) \quad &= p_\sigma \Pr(\tilde{t}_i > T|\theta_2, \sigma, BC_i, m_{ti} = 1) \\ &+(1 - p_\sigma) \Pr(\tilde{t}_i > T|\theta_2, \sigma, BC_i, m_{ti} = 0)\end{aligned} \tag{8}$$

Consider the following two assumptions. The first states that the probability of Type 2 patient receiving a mammogram is independent of whether that patient has breast cancer.

Assumption 3.

$$\Pr(m_{ti} = 1|\theta_2, \sigma, BC_i) = \Pr(m_{ti} = 1|\theta_2, \sigma) \tag{9}$$

Assumption 4.

$$\Pr(\tilde{t}_i > T|\theta_2, \sigma, BC_i, m_{ti}) = \Pr(\tilde{t}_i > T|\theta_2, BC_i, m_{ti}) \tag{10}$$

The second assumption states that conditional on receiving (or not receiving a mammogram) a Type 2 patient's survival probability is independent of the existence of the policy. That is, the impact of the policy is assumed to be only through the change in the probability that the patient receives a mammogram.

Proposition 1. Given the model and the assumptions above we can write

$$\begin{gathered}\Pr(\tilde{t}_i > T|\theta_2, \sigma = 1) - Pr(\tilde{t}_i > T|\theta_2, \sigma = 0) \\ = \\ \Pr(BC_i = 1|\theta_2)(p_\sigma - p)(\Pr(\tilde{t}_i > T|\theta_2, BC_i = 1, m_{ti} = 1) - \Pr(\tilde{t}_i > T|\theta_2, BC_i = 1, m_{ti} = 0))\end{gathered} \tag{11}$$

Given the assumptions made above, the question of interest turns on determining the difference in the survival probability for Type 2 patients with breast cancer who received a mammogram and those who did not.

As the probabilities on the right-hand side are not observed directly, the rest of the section presents the assumptions sufficient to identify these probabilities given the probabilities that are observed.

Each probability can be written as

$$\Pr(\tilde{t}_i > T|\theta_2, BC_i = 1, m_{ti}) = \sum_{s_0=1}^{S} \Pr(s_0|\theta_2, BC_i = 1, m_{ti}) \Pr(\tilde{t}_i > T|s_0, BC_i = 1, m_{ti}) \quad (12)$$

where s_0 is the initial stage of the disease at diagnosis.

Assumption 5.

$$\Pr(\tilde{t}_i > T|s_0, BC_i = 1, m_{ti}) = \Pr(\tilde{t}_i > T|s_0) \quad (13)$$

The use of a mammogram will be assumed to determine the probability distribution over the initial staging of the disease, but not the probability of survival conditional on the initial staging.

In the data we don't observe the "types" of the breast cancer patients. Rather we simply observe the probability distribution of the initial staging conditional on having breast cancer and having a mammogram in October/November (denoted "Oct") or having a mammogram in some other month (we will denote this "Aug").

Assumption 6.

$$\Pr(s_0|m_i = Oct, BC_i = 1) = 0.75 \Pr(s_0|m_i = Aug, BC_i = 1) + 0.25 \Pr(s_0|\theta_2, BC_i = 1, m_{ti} = 1) \quad (14)$$

That is, patients diagnosed through an "October" mammogram will be assumed to one of two populations. A population that has the same distribution of initial diagnoses as patients diagnosed with an "August" mammogram and a population of Type 2 patients. That is, we assume that all the added patients in October are Type 2 patients who do not have regular mammograms. Using this equation and noting that the distribution of initial staging is observed for the "August" mammograms and the "October" mammograms we can identify the probability distribution of interest.

Proposition 2. Given assumptions above, $\Pr(\tilde{t}_i > T|\theta_2, BC_i = 1, m_{ti} = 1)$ is a known function of observed probabilities.

Given the first two results, to determine the impact of a policy to induce greater screening, we need to determine the survival probability of a Type 2 women with breast cancer who does not receive a mammogram in the current period. For such a patient, there are four mutually exclusive possibilities. She may decide to have a mammogram, she may self-diagnose breast cancer, she may die of something unrelated to breast cancer or she may continue to live

undiagnosed. To determine the overall probability we need to determine the probability of each case and then the survival probability conditional upon that case being true.

Case 1. The patient decides to have a mammogram in period $\tau > t$.

The probability of a Type 2 women with breast cancer having a mammogram in a later period is assumed to be the same as for any Type 2 women. That is, having undiagnosed breast cancer doesn't change behavior in relation to the use of general screening.

Assumption 7.

$$\Pr(m_{\tau i} = 1|\theta_2, BC_i = 1) = \Pr(m_{ti} = 1|\theta_2) = p \tag{15}$$

From other data we know that

$$\begin{aligned} \Pr(m_{ti} = 1) = 0.75 \quad &= \Pr(m_{ti} = 1|\theta_1)\Pr(\theta_1) + \Pr(m_{ti} = 1|\theta_2)\Pr(\theta_2) \\ &= 1 - \pi + \pi p \end{aligned} \tag{16}$$

where $\Pr(\theta_2) = \pi$. So while p is not observed we know it lies between 0 and 0.75. If we can directly estimate π from the data, we can determine p. If we cannot directly estimate the fraction of Type 2 women, then probability of case 1 will be estimated up to a range.

Case 2. The patient self-diagnoses.

In order to determine the survival probability of a Type 2 patient that self-diagnoses, consider the following expansion.

$$\begin{aligned} \Pr(s_0|BC_i = 1, Diag_{\tau i} = 1) \quad &= \Pr(s_0|BC_i = 1, Diag_{\tau i} = 1, m_{\tau i} = 1)\Pr(m_{\tau i} = 1) \\ &+ \Pr(s_0|BC_i = 1, Diag_{\tau i} = 1, m_{\tau i} = 0)\Pr(m_{\tau i} = 0) \end{aligned} \tag{17}$$

Note that this can be re-arranged so that the probability of interest is an expression of observed probabilities.

$$\begin{aligned} &\Pr(s_0|BC_i = 1, Diag_{\tau i} = 1, m_{\tau i} = 0) \\ &= \tfrac{1}{\Pr(m_{\tau i}=0)}\left(\Pr(s_0|BC_i = 1, Diag_{\tau i} = 1) - \Pr(s_0|BC_i = 1, Diag_{\tau i} = 1, m_{\tau i} = 1)\Pr(m_{\tau i} = 1)\right) \end{aligned} \tag{18}$$

By definition of Type 1 and Type 2 women, the LHS is the distribution of initial staging for Type 2 women with breast cancer who are diagnosed through self-diagnosis.

To determine the probability of a Type 2 women with breast cancer being diagnosed through self-exam consider writing out the RHS using Bayes Rule.

$$\begin{aligned} &\Pr(s_0 = s|\theta_2, BC_i = 1, m_{\tau i} = 0, Diag_{\tau i} = 1) \\ &= \Pr(Diag_{\tau i} = 1|\theta_2, BC_i = 1, s_0 = s) \times \tfrac{\Pr(s_0=s|\theta_2, BC_i=1, m_{\tau i}=0)}{\Pr(Diag_{\tau i}=1|\theta_2, BC_i=1, m_{\tau i}=0)} \end{aligned} \tag{19}$$

where s refers to a particular stage of the disease.

Assumption 8.

$$\Pr(s_0 = s|\theta_2, BC_i = 1, m_{\tau i} = 0) = \Pr(s_0 = s|\theta_2, BC_i = 1, m_{\tau i} = 1) \tag{20}$$

Assumption 8 states that the underlying distribution of initial staging for Type 2 women with breast cancer is the same as for those women induced to have a mammogram. That is, the act of having a mammogram does not change the underlying distribution and there is no selection into mammograms after conditions on the women's type.

Assumption 9.

$$\Pr(Diag_{\tau i} = 1|m_{\tau i} = 0, s_0 = 4) = 1 \tag{21}$$

If we assume that patients with Stage 4 are diagnosed with probability equal to 1, irrespective of the screening technology used, we have

$$\Pr(Diag_{\tau i} = 1|\theta_2, BC_i = 1, m_{\tau i} = 0) = \frac{\Pr(s_0=4|\theta_2, BC_i=1, m_{\tau i}=0)}{\Pr(s_0=4|\theta_2, BC_i=1, m_{\tau i}=0, Diag_{\tau i}=1)} \tag{22}$$

The probability of a Type 2 women with breast cancer being diagnosed without a mammogram is equal to the ratio of the underlying probability of Stage 4 for these patients over the observed probability of Stage 4 for these patients once they have been diagnosed. The RHS is observed given assumptions above.

Case 3. The patient passes away prior to being diagnosed.

Finally we need to determine the probability that a Type 2 women with breast cancer passes away in the next period prior to being diagnosed. As the survival probability of women with undiagnosed breast cancer is unobserved we will need to make an assumption. Actually, we will present the results with different assumptions. For example, we could assume that the survival probability is the same for *all* women not diagnosed with breast cancer. Alternatively, we could assume that it is equal to the survival probability of women diagnosed with early stage breast cancer. In the data we see that women not diagnosed with breast cancer actually have *lower* survival rates than women diagnosed with early stage breast cancer.

Given these three cases and noting that surviving to the next period undiagnosed is the complement, then we can identify the probability of interest up to a range. This range depends on the identification of the probability that a Type 2 women with breast cancer will have a mammogram in one of the following periods and identification of the probability of such a women passing away prior to being diagnosed.

Proposition 3. Given the assumptions above, $\Pr(\tilde{t}_i > T|\theta_2, BC_i = 1, m_{ti} = 0)$ is identified up to the identification of p and the probability of passing away prior to being diagnosed.